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Daily Uganda Shilling/United States Dollar Exchange Rates Modeling by Box-Jenkins Techniques

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Abstract

A 180-point daily exchange rate series of the Uganda shilling (UGX) and the United States dollar (USD) covering from 25 August 2014 to 20 February 2015 is analyzed by seasonal Box-Jenkins methods. A time-plot of the series shows an upward trend indicating a relative depreciation of the UGX. A seven-day differencing of the series yield a series that is adjudged stationary by the Augmented Dickey Fuller (ADF) Test. However, its correlogram contradicts a stationarity hypothesis. A non-seasonal differencing of this series produces a series adjudged as stationary and having an autocorrelation function that suggests two models, namely: a SARIMA$(0,1,1)x(0,1,1)_7$ and a SARIMA$(0,1,1)x(1,1,1)_7$. Diagnostic checking methods used to compare the two models reveal that the former model is the more adequate model. Hence it is proposed that the exchange rates follow a SARIMA$(0,1,1)x(0,1,1)_7$ model. Forecasting might therefore be based on this model.

Keywords: Uganda shilling, United States Dollar, foreign exchange rates, SARIMA modeling.

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Introduction and literature review

For planning purpose a forecasting model for foreign exchange rates might be helpful. The purpose of this write-up is to propose such a model for daily Uganda

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Shilling (UGX) and the United State Dollar (USD). Many financial time series exhibit seasonality apart from being volatile. Such seasonal series may be modeled by seasonal Box-Jenkins or seasonal autoregressive integrated moving average (SARIMA) methods.

Of recent SARIMA methods have been used extensively for modeling such series. For instance, Mostafei and Sakhbakhsh (2011) observed that for the modeling of monthly Iraqi oil production SARIMA methods outdid SARFIMA methods. They ended up fitting a $SARIMA(0,1,0)x(0,0,1)_{12}$ model to the series. A $SARIMA(0,1,0)x(2,1,1)_{12}$ model is proposed for the forecasting of monthly para rubber export sales of Thailand by Pattranurakyothin and Kummungkit (2012). Bhatnagar *et al.* (2012) fitted a $SARIMA(0,0,1)x(0,1,1)_{12}$ model to monthly incidence of Dengue in Rajasthan. Etuk and Victor-Edema (2014) proposed the forecasting of monthly Nigerian bank prime lending rates on the basis of a $SARIMA(0,1,0)x(2,1,1)_{12}$ model. Quarterly Kenyan inflation rates have modeled as a $SARIMA(0,1,0)x(0,0,1)_4$ by Gikungu *et al.* (2015). Zhang *et al.* (2015) modeled quarterly mortalities of road traffic injuries by a $SARIMA(0,1,0)x(0,0,1)_4$ model.

Materials and methods

Data

The data for this write-up are 180 daily UGX/USD exchange rates downloaded from the website www.exchange-rates.org/history/UGX/USD/T accessed on Saturday 21 February 2015. It is to be interpreted as the amount of UGX in one USD.

Sarima models

A stationary time series {Xt} is said to follow an *autoregressive moving average model of order p and q* denoted by ARMA(p, q) if

$$X_t - \alpha_1 X_{t-1} - \alpha_2 X_{t-2} - \dots - \alpha_p X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \dots + \beta_q \varepsilon_{t-q} \quad (1)$$

where $\{\varepsilon_t\}$ is a white noise process and the α's and β's are constants such that the model is stationary as well as invertible.

Suppose model (1) is put as

$$A(L)X_t = B(L)\varepsilon_t \quad (2)$$

where A(L) is the autoregressive (AR) operator defined by $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \dots - \alpha_p L^p$ and B(L) is the moving average (MA) operator defined by $B(L) = 1 + \beta_1 L + \beta_2 L^2 + \dots + \beta_q L^q$ and $L^k X_t = X_{t-k}$.

In the event of series non-stationarity as is often the case, Box and Jenkins (1976) have proposed that with differencing up to a certain level the series may be stationary. Suppose for a particular time series $\{X_t\}$ d is the minimum differencing order for which it becomes stationary. Let $\{\nabla^d X_t\}$ be this d^{th} difference of the series. The operator $\nabla = 1-L$. If $\{\nabla^d X_t\}$ follows an ARMA(p,q) the series $\{X_t\}$ is said to follow an *autoregressive integrated moving average model of order p, d and q* denoted by ARIMA(p,d,q).

If the time series $\{X_t\}$ exhibits a seasonal pattern of period s, Box and Jenkins (1976) further proposed that it may be modeled as

$$A(L)\Phi(L^s)\nabla^d\nabla^D_s X_t = B(L)\Theta(L^s)\varepsilon_t \quad (3)$$

where $\Phi(L)$ and $\Theta(L)$ are the seasonal AR and MA operators respectively. The operator ∇_s is the seasonal difference operator defined by $\nabla_{s} = 1-L^s$ and D is the minimum order of seasonal differencing necessary for stationarity to be achieved. Suppose that they are P and Q degree polynomials respectively, model (3) is called a *seasonal autoregressive integrated moving average model of order p, d, q, P, D, Q and s* denoted by SARIMA(p,d,q)x(P,D,Q)$_s$.

Sarima model fitting

The fitting of model (3) starts with the determination of the orders p, d, q, P, D, Q and s. The seasonal period s may be suggestive from the glaring seasonal nature of the time series as with rainfall or atmospheric temperature series. Otherwise some preliminary inspection of the series could reveal a seasonal pattern. Moreover the correlogram of a seasonal series exhibits some seasonal pattern of the same periodicity.

The AR orders p and P are estimated by the non-seasonal and the seasonal cut-off points of the partial autocorrelation functions (PACF) respectively. Similarly, the MA orders q and Q are estimated by the non-seasonal and the seasonal cut-off points of the autocorrelation function (ACF) respectively. It is often enough to choose the differencing orders d and D such that their sum is at most equal to 2. Seasonality may be tested using the augmented Dickey-Fuller (ADF) test.

Parameter estimation is based on the application of nonlinear optimization techniques like the least squares and the maximum likelihood procedures. Model comparison will be done using Akaike information criterion (AIC).

Computer software

The statistical and econometric software eviews 7 shall be used for all analytical work in this write-up. It is based on the least squares criterion.

Results and discussion

The time plot in Figure 1 of the realization called UXUD herein shows an upward trend which means that UGX relatively depreciates in the given interval of time. Preliminary data inspection reveals that weekly minimums tend to lie on Mondays and the maximums on Sundays which is an evidence of weekly seasonality. Therefore, a seven-day differencing of UXUD yields a series called SDUXUD which has a generally horizontal trend (See Figure 2). The ADF test statistic for UXUD and SDUXUD are –0.88 and -3.88. The 1%, 5% and 10% critical values are -3.47, -2.88 and

-2.58 respectively. Hence the test declares UXUD non-stationary but SDUXUD stationary.

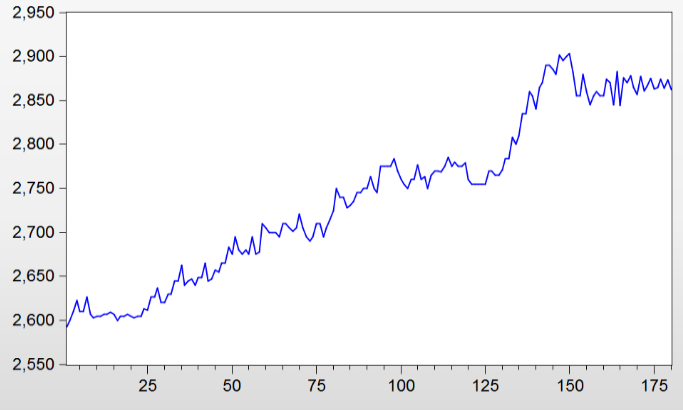


FIGURE 1: UXUD

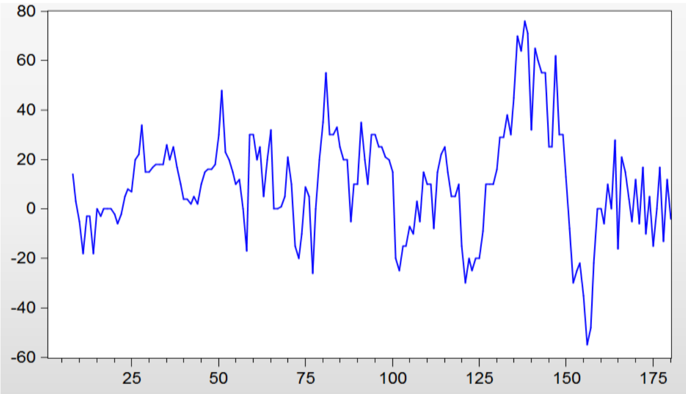


FIGURE 2: SDUXUD

However the correlogram of SDUXUD in Figure 3 does not seem to confirm this stationarity hypothesis. A non-seasonal differencing of SDUXUD yields DSDUXUD which has a generally flat trend as can be seen in Figure 4 and a correlogram in Figure 5 that supports a stationarity hypothesis. Moreover two SARIMA models are immediately suggestive: a SARIMA(0,1,1)x(0,1,1)$_7$ and a SARIMA(0,1,1)x(1,1,1)$_7$.

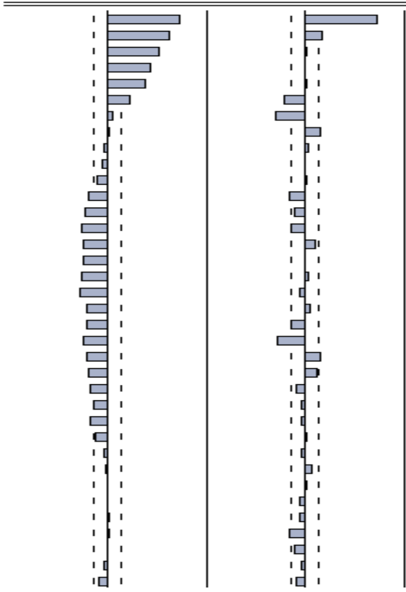
Estimation of the SARIMA(0,1,1)x(0,1,1)$_7$ model as summarized in Table 1 yields the model

$$X_t + ..2981\varepsilon_{t-1} - .9401\varepsilon_{t-7} - .2648\varepsilon_{t-8} = \varepsilon_t \quad (4)$$

whereas that of the SARIMA(0,1,1)x(1,1,1)$_7$ as summarized in Table 2 yields

$$X_t - .0437X_{t-7} + .3055\varepsilon_{t-1} + .9354\varepsilon_{t-7} - .2702\varepsilon_{t-8} = \varepsilon_t \quad (5)$$

Clearly model (4) does better than model (5) on all counts. That is, it has lower AIC, Schwarz criterion and Hannan-Quinn criterion and higher R^2 than model (5). Moreover its residuals follow a normal distribution (See Figure 6).



	AC	PAC	Q-Stat	Prob
1	0.760	0.760	101.64	0.000
2	0.651	0.174	176.63	0.000
3	0.546	0.014	229.80	0.000
4	0.457	-0.008	267.16	0.000
5	0.388	0.012	294.26	0.000
6	0.235	-0.224	304.29	0.000
7	0.045	-0.299	304.66	0.000
8	0.017	0.170	304.71	0.000
9	-0.036	0.039	304.95	0.000
10	-0.064	0.008	305.71	0.000
11	-0.100	0.016	307.57	0.000
12	-0.204	-0.171	315.42	0.000
13	-0.233	-0.104	325.65	0.000
14	-0.263	-0.141	338.83	0.000
15	-0.251	0.108	350.91	0.000
16	-0.256	0.006	363.58	0.000
17	-0.269	0.027	377.65	0.000
18	-0.290	-0.054	394.13	0.000
19	-0.223	0.058	403.90	0.000
20	-0.221	-0.145	413.54	0.000
21	-0.253	-0.286	426.31	0.000
22	-0.216	0.165	435.71	0.000
23	-0.191	0.116	443.05	0.000
24	-0.173	-0.084	449.14	0.000
25	-0.149	-0.030	453.68	0.000
26	-0.177	-0.043	460.13	0.000
27	-0.119	0.019	463.06	0.000
28	-0.042	-0.037	463.44	0.000
29	-0.023	0.068	463.55	0.000
30	0.004	0.014	463.55	0.000
31	0.001	-0.060	463.55	0.000
32	0.015	-0.061	463.60	0.000
33	0.023	-0.159	463.71	0.000
34	-0.006	-0.104	463.72	0.000
35	-0.030	-0.045	463.92	0.000
36	-0.098	-0.086	466.04	0.000

Figure 3: Correlogram of sduxud

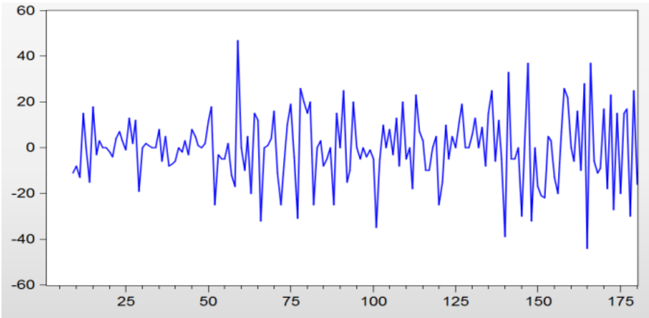
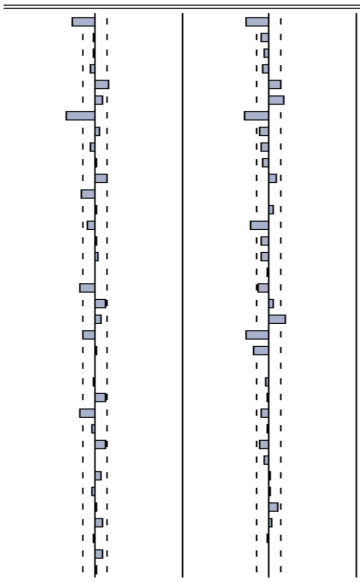


FIGURE 4: DSDUXUD



	AC	PAC	Q-Stat	Prob
1	-0.268	-0.268	12.533	0.000
2	-0.018	-0.097	12.591	0.002
3	-0.019	-0.054	12.652	0.005
4	-0.052	-0.080	13.124	0.011
5	0.170	0.142	18.314	0.003
6	0.088	0.188	19.706	0.003
7	-0.347	-0.291	41.595	0.000
8	0.063	-0.115	42.313	0.000
9	-0.062	-0.094	43.016	0.000
10	0.023	-0.072	43.114	0.000
11	0.139	0.091	46.700	0.000
12	-0.157	0.004	51.310	0.000
13	0.009	0.046	51.327	0.000
14	-0.087	-0.205	52.765	0.000
15	0.022	-0.092	52.857	0.000
16	0.032	-0.091	53.051	0.000
17	0.007	-0.012	53.061	0.000
18	-0.183	-0.131	59.598	0.000
19	0.131	0.065	62.948	0.000
20	0.074	0.201	64.018	0.000
21	-0.144	-0.264	68.101	0.000
22	0.015	-0.188	68.146	0.000
23	0.007	0.003	68.156	0.000
24	-0.016	-0.041	68.210	0.000
25	0.116	-0.024	70.945	0.000
26	-0.176	-0.092	77.267	0.000
27	-0.040	-0.010	77.603	0.000
28	0.118	-0.114	80.475	0.000
29	-0.008	-0.060	80.487	0.000
30	0.071	0.012	81.552	0.000
31	-0.028	0.009	81.714	0.000
32	0.011	0.103	81.741	0.000
33	0.090	0.039	83.466	0.000
34	-0.023	-0.014	83.579	0.000
35	0.092	0.001	85.413	0.000
36	0.023	0.007	85.531	0.000

Figure 5: Correlogram of dsduxud

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Table 1: Estimation of the sarima $(0,1,1)x(0,1,1)_7$ model

Dependent Variable: DSDUXUD				
Variable	Coefficient	Std. Error	T-statistic	Prob.
MA(1)	-0.298192	0.073181	-4.074715	0.0001
MA(7)	-0.940056	0.018853	-49.86336	0.0000
MA(8)	0.264799	0.072051	3.675153	0.0003
R-squared	0.483793	Mean dep. var	-0.104651	
Adjusted R-squared	0.477684	S.D. dep. var	15.25497	
S.E. of regression	11.02499	Akaikae info criter	7.655493	
Sum squared resid	20542.00	Schwarz criterion	7.710391	
Log likelihood	-655.3724	Hannan-Quinn crit	7.677767	
Durbin-Watson stat	2.024825			
Inverted MA Roots .99	.62 ±.77i	.28	-.22±.97i	-0.89±-43i

Table 2: estimation of the Sarima $(0,1,1)x(1,1,1)_7$ model

Dependent Variable: DSDUXUD				
Variable	Coefficient	Std. Error	T-statistic	Prob.
AR(7)	0.043737	0.083288	0.525122	0.6002
MA(1)	-0.305488	0.075603	-4.040688	0.0001
MA(7)	-0.935388	0.022796	-41.03364	0.0000
MA(8)	0.270197	0.074342	3.634519	0.0004
R-squared	0.472921	Mean dep. var	-0.024242	
Adjusted R-squared	0.463100	S.D. dep. var	15.35513	
S.E. of regression	11.25123	Akaike info criter	7.702776	
Sum squared resid	20381.02	Schwarz criterion	7.778072	
Log likelihood	-631.4790	Hannan-Quinn crit	7.733341	
Durbin-Watson stat	2.011882			
Inverted AR Roots .64 .40±.50i -.14±.62i -.58±.28i				
Inverted MA Roots .99 .62±.77i .29 -.22±.97i -.89±.43i				

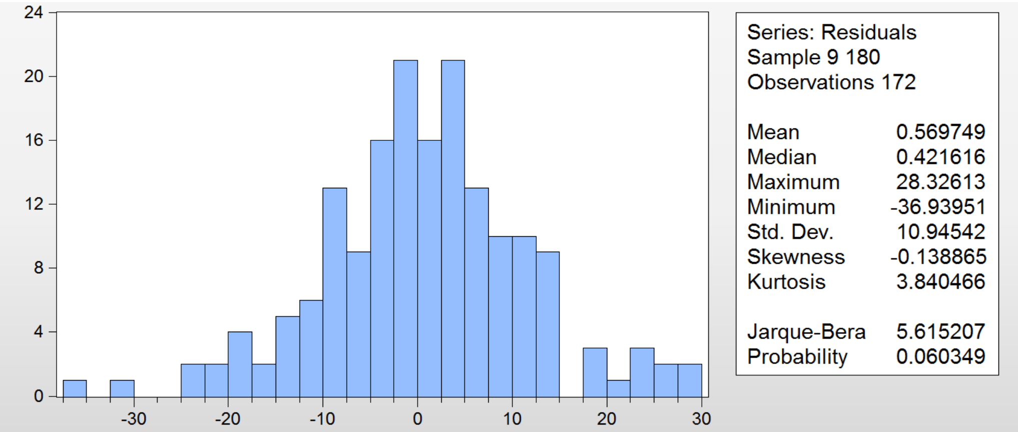

Figure 6: histogram of Sarima $(0,1,1)x(0,1,1)_7$ residuals

Conclusion

It may be concluded that daily UGX-USD exchange rates follow a SARIMA(0,1,1)x$(0,1,1)_7$ model. Forecasting of the series may be based on this model.

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